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Extracting inter-area oscillation modes using local measurements and data-driven stochastic subspace technique

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Abstract In this paper, a data-driven stochastic subspace identification (SSI-DATA) technique is proposed as an advanced stochastic system identification (SSI) to extract the inter-area oscillation modes of a power system from wide-area measurements. For accurate and robust extraction of the modes' parameters (frequency, damping and mode shape), SSI has already been verified as an effective identification algorithm for output-only modal analysis. The new feature of the proposed SSI-DATA applied to inter-area oscillation modal identification lies in its ability to select the eigenvalue automatically. The effectiveness of the proposed scheme has been fully studied and verified, first using transient stability data generated from the IEEE 16-generator 5-area test system, and then using recorded data from an actual event using a Chinese wide-area measurement system (WAMS) in 2004. The results from the simulated and recorded measurements have validated the reliability and applicability of the SSI-DATA technique in power system low frequency oscillation analysis.

Keywords Data-driven stochastic subspace identification (SSI-DATA), Power system inter-area oscillation, Wide-area measurement systems (WAMS), Modal analysis

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1 Introduction

Extracting and quantifying dynamic behavior from observed oscillations presents a significant challenge in the rapid development of modern power systems [1]. With advances in computing and data communication technologies, a wide-area measurement system (WAMS) becomes a powerful tool to provide real-time measurements for analyzing inter-area power swing dynamics in large interconnected power systems [2, 3].

So far, published methods in inter-area oscillation monitoring and analysis utilizing WAMS data can be divided into two groups. In the first group, spectral analysis approaches such as Prony and Fourier spectral and block processing techniques have been successfully used on complex WAMS data sets to extract modal information [4–7]. Such approaches also include the use of wavelet-based spectral analysis [8] and the modified Yule-Walker method to estimate low-frequency modes from simulated data set and actual ambient power system data [7]. However, as the measured data set grows, it becomes difficult to accurately extract the mode and its parameters because of noise and non-stationary phenomena. Recently, techniques of nonlinear and non-stationary analysis based on non-stationary autoregression and empirical mode decomposition (EMD) have been refined to more accurately monitor inter-area oscillations [9–12].

In the second group, system identification methods based on the state space have been shown to perform well on ambient noise signals. In [13], the proper orthogonal decomposition (POD) to determine the eigenvalues of the covariance matrix of power system oscillation signals has been shown to be suitable for multiple signals. In [14], the eigensystem realization algorithm (ERA) combining with linear filter decomposition and Teager-Kaiser energy

(TKE) has been adopted to identify the modal parameters from measured data. An alternative technique for obtaining modal parameters from multiple measured signals is the stochastic subspace identification (SSI) method. In [15] and [16], SSI was used to extract the critical modes of the system from simulation results of test cases. Some well-known techniques such as QR factorization, least squares and singular value decomposition (SVD) have been utilized in SSI and all are regarded as robust and accurate system identification methods for output-only modal analysis. The automation of the eigenvalue selection process would provide a lot of advantages for modal identification.

In this paper, the data-driven stochastic subspace identification (SSI-DATA) technique combined with automation of the eigenvalue selection process is proposed to extract the inter-area oscillation modal parameters from wide-area measurements. Power system oscillations and the SSI-DATA algorithm will first be reviewed in Sections 2 and 3. Then, the application of SSI-DATA to inter-area oscillation modal identification is briefly described in Section 4. To validate the effectiveness of the proposed technique, simulated data generated from the IEEE 16-generator 5-area test system and real data extracted from the post-mortem analysis of the record of an actual event in China in 2004 were fully investigated and the identified modes verified in Section 5. The focus of these case studies was on the extraction of inter-area power swing dynamics.

2 Power system oscillation

Power system oscillation may be triggered by many incidents in the system. Most power oscillations are suppressed by natural damping of the system, but system collapse can be caused by undamped oscillation. Theoretically, power oscillations are due to the rotor acceleration or deceleration following a change in active transfer from a generator.

It is generally appreciated that a power system may be linearized at an operating point and described in state space form as [17]:

$$\begin{cases} \boldsymbol{x} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u} \\ \boldsymbol{y} = \boldsymbol{C}\boldsymbol{x} + \boldsymbol{D}\boldsymbol{u} \end{cases} \tag{1}$$

where $\boldsymbol{x}$ is the state vector; $\boldsymbol{y}$ is the output vector; $\boldsymbol{u}$ is the input vector; $\boldsymbol{A}$ is the state matrix; $\boldsymbol{B}$ is the input matrix; $\boldsymbol{C}$ is the output matrix; and $\boldsymbol{D}$ is the feed-forward matrix.

The power oscillation properties may be obtained through eigen decomposition of the state matrix $\boldsymbol{A}$. For small-signal stability of power system, the i^{th} eigenvalue is defined as the i^{th} oscillation mode:

$$\lambda_i = \sigma_i \pm \mathrm{j}\omega_i \tag{2}$$

The corresponding oscillation frequency f_i and damping ratio ξ_i are:

$$\begin{cases} f_i = \omega_i / 2\pi \\ \xi_i = -\sigma_i / \sqrt{\sigma_i^2 + \omega_i^2} \end{cases} \tag{3}$$

The shape of mode λ_i is derived from the elements of the corresponding right eigenvector of the state matrix $\boldsymbol{A}$, combining with the original state variables.

Therefore, the mode parameters including frequency, damping and the corresponding mode shape may be identified by estimating the state matrix of the linearized power system, and its eigen decomposition, from measured data. With the data-driven SSI technique proposed in Section 3, mode parameters are obtained by identifying the state and output matrices firstly and then performing eigen decomposition.

3 Data-driven stochastic subspace identification

SSI-DATA [18, 19] is one of the effective experimental modal analysis methods and has been developed in recent years because of its numerical simplicity, SSI-DATA's state-space form and the robustness of the techniques used in the algorithm.

3.1 Stochastic state-space model

The discrete stochastic state space model can be obtained after sampling at discrete time intervals. Supposing the discrete stochastic state-space model is described as [18]:

$$\begin{cases} \boldsymbol{x}_{k+1} = \boldsymbol{A}_d \boldsymbol{x}_k + \boldsymbol{w}_k \\ \boldsymbol{y}_k = \boldsymbol{C}\boldsymbol{x}_k + \boldsymbol{v}_k \end{cases} \tag{4}$$

where $\boldsymbol{x}_k$ is the discrete time state vector at time step k; $\boldsymbol{y}_k$ is the output vector; $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ are stochastic terms with zero mean noise $E(\boldsymbol{w}_k) = E(\boldsymbol{v}_k) = 0$.

In (4), the stochastic terms $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ are unknown, but they are assumed to have a discrete white noise nature with an expected value of zero and the following covariance matrices:

$$\boldsymbol{E}\left[\begin{pmatrix} \boldsymbol{w}_p \\ \boldsymbol{v}_q \end{pmatrix} \begin{pmatrix} \boldsymbol{w}_p^{\mathrm{T}} & \boldsymbol{v}_q^{\mathrm{T}} \end{pmatrix}\right] = \begin{pmatrix} \boldsymbol{Q} & \boldsymbol{S} \\ \boldsymbol{S}^{\mathrm{T}} & \boldsymbol{R} \end{pmatrix} \delta_{pq} \tag{5}$$

where $\boldsymbol{E}(\cdot)$ is the expected value operator; δ_{pq} is the Kronecker delta.

3.2 Data-driven stochastic subspace identification

The measured data y_i, which are generator outputs in this paper, are divided into two parts representing past and future, and formed into an output block Hankel matrix [19], $\boldsymbol{H}$:

$$\boldsymbol{H}=\boldsymbol{Y}_{0,2i-1}=\left[\begin{array}{cccc} y_0 & y_1 & \cdots & y_{j-1}\\ y_1 & y_2 & \cdots & y_j\\ \cdots & \cdots & \cdots & \cdots\\ y_{i-1} & y_i & \cdots & y_{i+j-2}\\ \hline y_i & y_{i+1} & \cdots & y_{i+j-1}\\ y_{i+1} & y_{i+1} & \cdots & y_{i+j}\\ \cdots & \cdots & \cdots & \cdots\\ y_{2i-1} & y_{2i} & \cdots & y_{2i+j-2}\end{array}\right]=\left[\frac{\boldsymbol{Y}_{0,i-1}}{\boldsymbol{Y}_{i,2i-1}}\right]=\frac{\boldsymbol{Y}_p}{\boldsymbol{Y}_f} \tag{6}$$

where $\boldsymbol{Y}_p=\boldsymbol{Y}_{0,i\text{-}1}$, $\boldsymbol{Y}_f=\boldsymbol{Y}_{i,2i\text{-}1}$ are the past and future parts respectively of the block Hankel matrix with $i=2n$; n is the system order and j is the number of measured data. $\boldsymbol{Y}_p$ (the past inputs) and $\boldsymbol{Y}_f$ (the future inputs) are defined by splitting $\boldsymbol{Y}_{0,2i\text{-}1}$ into two equal parts of i rows. By advancing the boundary i in the Hankel matrix, new past and future parts can be obtained, which are $\boldsymbol{Y}_p^+=\boldsymbol{Y}_{0,i}$ and $\boldsymbol{Y}_f^-=\boldsymbol{Y}_{i+1,2i\text{-}1}$.

The projections of the future row spaces to the past row spaces can be obtained:

$$\boldsymbol{O}_i=\boldsymbol{Y}_f/\boldsymbol{Y}_p \tag{7}$$

The SVD of the weighted projection is calculated as:

$$\boldsymbol{W}_1\boldsymbol{O}_i\boldsymbol{W}_2=\boldsymbol{USV}^{\mathrm{T}}=[\boldsymbol{U}_1\boldsymbol{U}_2]\begin{bmatrix}\boldsymbol{S}_1 & 0\\ 0 & 0\end{bmatrix}\begin{bmatrix}\boldsymbol{V}_1^{\mathrm{T}}\\ \boldsymbol{V}_2^{\mathrm{T}}\end{bmatrix} \tag{8}$$

where $\boldsymbol{W}_1=((1/j)\boldsymbol{Y}_f\boldsymbol{Y}_f^{\mathrm{T}})^{-(1/2)}$ and $\boldsymbol{W}_2=[\boldsymbol{I}]_{jxj}$ are both weighting matrices; $\boldsymbol{U}$ and $\boldsymbol{V}$ are unitary matrices resulting from the SVD process; $\boldsymbol{S}$ is a diagonal matrix containing the singular values which indicate the rank of the matrix (the order of system). The reduced diagonal matrix $\boldsymbol{S}_1$ is obtained by keeping only the part of the matrix $\boldsymbol{S}$ with non-zero diagonal elements.

Extended observables matrices are constructed as:

$$\boldsymbol{\Gamma}_{\mathbf{i}}=\boldsymbol{W}_1^{-1}\boldsymbol{U}_1\boldsymbol{S}_1^{1/2} \tag{9}$$

$$\boldsymbol{\Gamma}_{i-1}=\boldsymbol{\Gamma}_i \tag{10}$$

The Kalman filter state sequences are obtained from (7–10):

$$\hat{\boldsymbol{X}}_i=\boldsymbol{\Gamma}_i^{\dagger}O_i \tag{11}$$

$$\hat{\boldsymbol{X}}_{i+1}=\boldsymbol{\Gamma}_{i-1}^{\dagger}O_{i-1} \tag{12}$$

where † denotes the pseudo inverse of the matrix. The state and output matrices can then be determined as:

$$\begin{bmatrix}\boldsymbol{A}_d\\ \boldsymbol{C}\end{bmatrix}=\begin{bmatrix}\hat{\boldsymbol{X}}_{i+1}\\ \boldsymbol{Y}_{i|i}\end{bmatrix}\hat{\boldsymbol{X}}_i^{\dagger} \tag{13}$$

Now the realizations of the system matrices $\boldsymbol{A}_d$ and $\boldsymbol{C}$ are identified collectively from all measured signals instead of one particular individual signal. Thus, the modal parameters can be obtained through the eigen decomposition of the state matrix $\boldsymbol{A}_d$:

$$\begin{cases}\boldsymbol{A_d}=\boldsymbol{\psi\Lambda\psi}^{-1}\\ \boldsymbol{\varphi}=\boldsymbol{C\psi}\end{cases} \tag{14}$$

where $\boldsymbol{\psi}$ is the complex eigenvector matrix; $\boldsymbol{\varphi}$ is the mode shape matrix; and $\boldsymbol{\Lambda}=\mathrm{diag}(\eta_1,\ \eta_2,\ \ldots,\ \eta_n)$ is a diagonal matrix composed of the complex poles (eigenvalues) of the system. It shall be noted from (6–14) that a different combination of j and n will give a different state matrix, and furthermore will lead to a different set of modal parameters. Therefore, modal parameters should be derived from a series of combinations, rather than a single combination.

3.3 Determination of the modal parameters and estimation of system order

Mode identification is achieved by adjusting the model order n and the number of data j to achieve convergent eigenvalues. The order of the system is an essential piece of information for modal identification and analysis, but it is often not available, and a good engineering estimate is needed. Here, a simple but effective automatic process is proposed. Firstly, the range of model order to be estimated is specified; then starting from the lower bound, the poles (eigenvalues) corresponding to a given model order n are computed and compared to the poles (eigenvalues) of a one-order-lower model. Stability limits are defined by [20]:

$$l_{lim,f}=\left|f^n-f^{n-1}\right|/f^n \tag{15}$$

$$l_{lim,\xi}=\left|\xi^n-\xi^{n-1}\right|/\xi^n \tag{16}$$

If the frequency and the damping ratio differences are within the desired tolerance, the pole is labelled as a stable one [19]; otherwise, the model order n will be incremented and the procedure repeated until the model order is determined or the upper bound is reached. The modal frequency (f_i) and damping (ξ_i) corresponding to each pole (eigenvalue) can then be calculated by:

$$\begin{cases}f_i=\sqrt{a_i^2+b_i^2}/2\pi\\ \xi_i=-a_i/\sqrt{a_i^2+b_i^2}\end{cases} \tag{17}$$

where a_i and b_i are real and imaginary parts of the continuous time eigenvalue defined by [19]:

$$\lambda_i = a_i \pm \mathrm{j}b_i = \ln(\eta_i)/\Delta t \tag{18}$$

where η_i is the discrete time eigenvalue, corresponding to the ith mode.

The ith mode shape can be computed from:

$$\boldsymbol{\varphi}_i = \boldsymbol{C}\boldsymbol{\psi}_i \tag{19}$$

where $\boldsymbol{\psi}_i$ is the right eigenvector corresponding to the ith mode η_i.

For an inter-area oscillation analysis, in addition to the frequency and damping ratio, it's equally important to extract the corresponding mode shape. As mentioned before, the frequency, damping ratio and mode shape can be identified at the same time by using SSI-DATA. This method is well suited to analyze inter-area oscillation due to its ability to extract the mode shapes, the oscillation frequencies, and their damping identified from multiple dynamic responses, such as generator speed and active power oscillating signals.

4 Application of SSI-DATA in power system analysis

Based on the SSI-DATA described in previous section, a scheme for extraction of the inter-area oscillation modes from multiple generator oscillating signals is developed as shown in Fig. 1. The three main challenges in its practical implementation are discussed below.

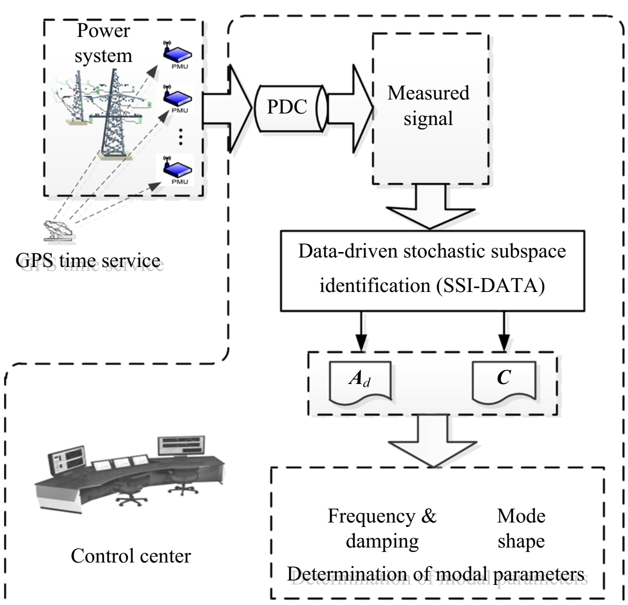


Fig. 1 Overview of the proposed SSI-DATA based scheme

4.1 Selection of measured system outputs

It should be noted that modal parameters including frequency, damping and mode shape are defined in terms of generator states which have historically been difficult to establish in real time. Phasor measurement units (PMUs) are now capable of providing real-time measurements of the operational state of a power system using satellite-triggered time stamps. PMUs installed at generator buses shall be used by operators to measure the system output including the generator states. Other data, such as phase angles and voltages, which are useful for monitoring and controlling, can be obtained.

Hence, modal parameters including frequency, damping and mode shape derived from a group of carefully selected measured system outputs are used to estimate the true mode parameters.

4.2 Placing PMUs for monitoring inter-area oscillation

Theoretically, it would be the best to have PMUs placed on all the generator buses, it would be sufficient in practice to have at least one PMU placed in each area as generators in a given area would often swing coherently [11]. In order to improve measurement reliability, it is recommended to have PMUs installed at the terminals of the main generators which have relatively larger rated capacity in each area. For this application of extracting the dominant inter-area modes, it is assumed that PMUs will be available at the terminals of two large generators in each area [21].

4.3 Scheme of modal parameters identification

When suitable measured system outputs are selected, inter-area oscillation modal parameters can be estimated by using the following scheme.

Step 1: Form the output block Hankel matrix, $\boldsymbol{H}$ in (6) with a given set of measured data obtained by PMU

Step 2: Determine the projection matrices in (7) with the model order n set to the lower bound value as defined by the user

Step 3: Calculate the extended observable matrices in (8) and (9)

Step 4: Compute the system matrices $\boldsymbol{A}_d$ and $\boldsymbol{C}$ using (13)

Step 5: By employing (17) and (18), estimate the modal parameters through the eigen decomposition of the state matrix $\boldsymbol{A}_d$

Step 6: If the frequency limit $l_{lim,f}$ and the damping limit $l_{lim,\xi}$ are below their preset tolerance values, the system order is determined; otherwise, increment the model order n and return to Step 1. Typically, tolerances of 1% for frequencies and 5% for damping [20] have been used for this research

Step 7: Report the model order, poles (eigenvalues) and their corresponding modal parameters

5 Simulation and discussion

In this section, case studies based on the simulated IEEE 68-bus 5-area test system and actual event data are presented to investigate the performance of the proposed scheme.

5.1 IEEE 68-bus 5-area test system

Transient stability simulation data generated from the IEEE 68-bus 5-area test system is first used to evaluate the performance of the proposed approach in extracting the features of the inter-area oscillation from measurements of interconnected power systems. The details of the system are given in [22].

In Area A, the rated capacity of G6 and G9 are larger than that of other generators, and PMUs are therefore sited on G6 and G9 following the guidelines given in Section 4.2. Likewise, PMUs are sited on G12 and G13 in Area B. Areas C, D and E have only one equivalent generator each, thus PMUs are sited on G14 in Area C, G15 in Area D and G16 in Area E.

Firstly, the theoretical modal parameters (including frequency, damping and mode shape) of inter-area oscillation were obtained by the QR method. As observed from Table 1 and Fig. 2, four theoretical inter-area oscillation modals exist in this test system. Fig. 2 shows that for Mode 1, generators 1～13 of Areas A and B oscillate against generators 14～16 of Areas C, D and E. In other words, for Mode 1, the oscillation area cluster is Areas A and B against Areas C, D and E. By the same token, the oscillation area clusters of the remaining inter-area modes are Areas C and D against Area E, Area A against Area B, and Areas C and E against Area D. In order to normalize mode

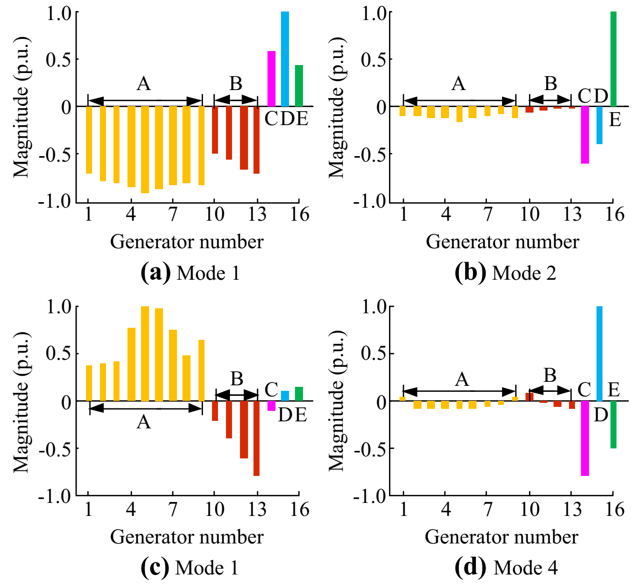


Fig. 2 Theoretical inter-area mode shapes of IEEE 16-generator 5-area test system

shapes, each right eigenvector corresponding to the inter-area modes is divided by the maximum magnitude among all the right eigenvectors.

The following two contingency scenarios were selected for analysis.

Case 1: A three-phase fault with duration of 0.05 s is applied at Bus 49

Case 2: A 0.15 p.u step disturbance with duration of 0.1 s is applied to the reference voltage of the exciter at G8

Detailed numerical simulations for Cases 1 and 2 were performed with a time step of 0.01 s to generate the data set used in the SSI-DATA method. Figure 3 depicts the active power deviation from the steady state operating point of generators measured via PMUs in Cases 1 and 2 over a time window of 10 s after disturbance.

Since inter-area oscillation modes are the main focus of this paper, only the modal parameters of inter-area oscillations with frequency in the range of 0.2 Hz to 0.7 Hz (in 50 Hz system) were computed. Table 2 shows the

Table 1 Theoretical modal parameters of inter-area oscillation

Mode No.	Frequency (Hz)	Damping	Oscillation area cluster
1	0.6995	0.0469	Area A and Area B against Area C, Area D and Area E
2	0.6428	0.0468	Area C and Area D against Area E
3	0.5531	0.0339	Area A against Area B
4	0.3798	0.0861	Area C and Area E against Area D

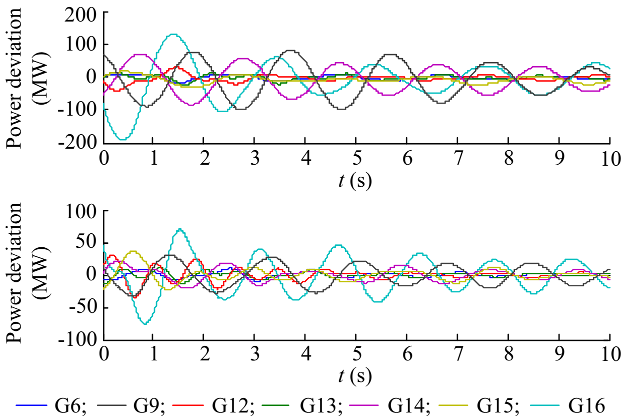


Fig. 3 Active power deviation of selected generator

Table 2 Modes identified by applying SSI-DATA to simulated data

Case	Mode no.	Frequency (Hz)	Damping
1	1	0.6850	0.0447
	2	0.5642	0.0360
2	1	0.6384	0.0488
	2	0.5312	0.0303

identified results obtained with the proposed SSI-DATA method applied to the simulated data. Following the eigen decomposition for the estimation of frequency and damping, the mode shapes corresponding to the identified inter-area oscillation modes were extracted and shown in Fig. 4 for both Cases 1 and 2.

Modes are excited to different degrees according to the disturbance that causes them. Modes with poor damping are more noticeable. As shown in Table 2, it is clear that all the modes detected from numerical data using the SSI-DATA technique are the theoretical inter-area modes, but with lower damping. As noted above, G6 and G9 were selected as the representatives of Area A while G12 and G13 were selected as the representatives of Area B. Comparing Figs. 2, 4, it is observed that the estimated swing patterns and mode shapes generally agree with the theoretical ones, in particular for the modes with similar frequency, for example 0.5531 Hz, 0.5642 Hz and 0.5312 Hz.

Compared with traditional methods, the main advantage of the proposed SSI-DATA approach is that the mode shape can be extracted following the identification of frequency and damping. This is because the state matrix and the output matrix can also be estimated in the SSI-DATA technique and, being derived from multiple inputs, they are likely to reflect the dynamic behavior correctly.

5.2 Northeast China power grid

The event data used in this study describes the dynamic response of a three-phase fault on a 500 kV bus in the Northeast China Power Grid. The event was recorded by a WAMS for a duration of about 40 s on March 24, 2004, starting at 13:28:25 local time, and the power swings are plotted in Fig. 5. Selected PMU recordings represented PMU measurements of generators in the study area. The data samples were acquired at a sampling period of 2 ms over a 5 s window period.

Based on the measured data at various locations, the Prony spectral analysis method [23], Matrix Pencil [24], estimation of signal parameters via rotational invariance techniques (ESPRIT) [25] and HHT [10] were firstly used to determine dynamic trends of the selected generators with results shown in Table 3 and Fig. 6. The two identified

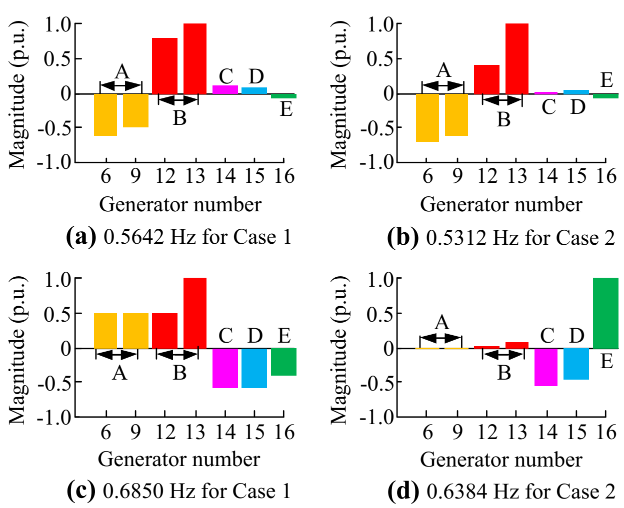


Fig. 4 Normalized mode shapes of inter-area modes identified by applying SSI-DATA to simulated data

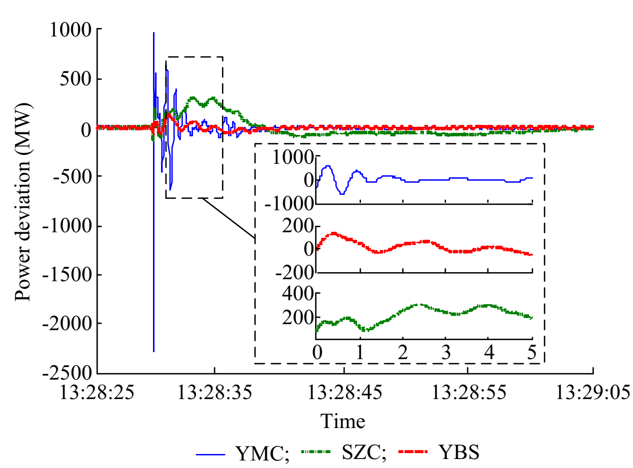


Fig. 5 Temporal evolution of selected system signals

Table 3 Extracted modal information using conventional method

PMU	Method	Mode no.	Frequency (Hz)	Damping
YMC	Prony	1	1.3100	0.0921
		2	0.5302	0.1307
	Matrix pencil	1	1.3144	0.1001
		2	0.5336	0.1328
	ESPRIT	1	1.3202	0.0970
		2	0.5234	0.1362
	HHT	1	1.3010	0.0986
		2	0.5197	0.1325
YBC	Prony	2	0.5309	0.1322
	Matrix pencil	2	0.5210	0.1282
	ESPRIT	2	0.5166	0.1389
	HHT	2	0.5247	0.1304
SZC	Prony	2	0.4590	0.1351
	Matrix pencil	2	0.4658	0.1225
	ESPRIT	2	0.4688	0.1295
	HHT	2	0.4633	0.1268

dominant modes are at about 0.5 Hz and 1.3 Hz respectively.

Further analysis was then conducted with the proposed SSI-DATA technique. The frequency and damping of the modes estimated using SSI-DATA technique are given in Table 4. As shown in Table 4, two oscillation modes at 1.3201 Hz and 0.5153 Hz were extracted. The results obtained using the SSI-DATA technique are consistent with the other mode extraction methods while the corresponded mode shapes as shown in Fig. 7 were also computed using the proposed SSI-DATA technique.

It can be seen that the modes extracted from the WAMS data using the proposed SSI-DATA technique are the typical local mode and the inter-area mode. For mode 1, a local oscillation in the system containing generator YMC is excited. The second mode reveals an inter-area mode at 0.51 Hz (lower frequency) between this system and the system containing generators YBC and SZC.

Further study on the measured signals and the extracted modal information reveals that the oscillation died down rapidly due to good damping. This matches with the fact that, in the studied system, a power system stabilizer (PSS) was installed at all generators with capacity over 100 MW. This shows that the provision of mode shape estimation in the proposed SSI-DATA technique is particularly useful for the analysis of oscillations in large-scale interconnected power system using actual event data.

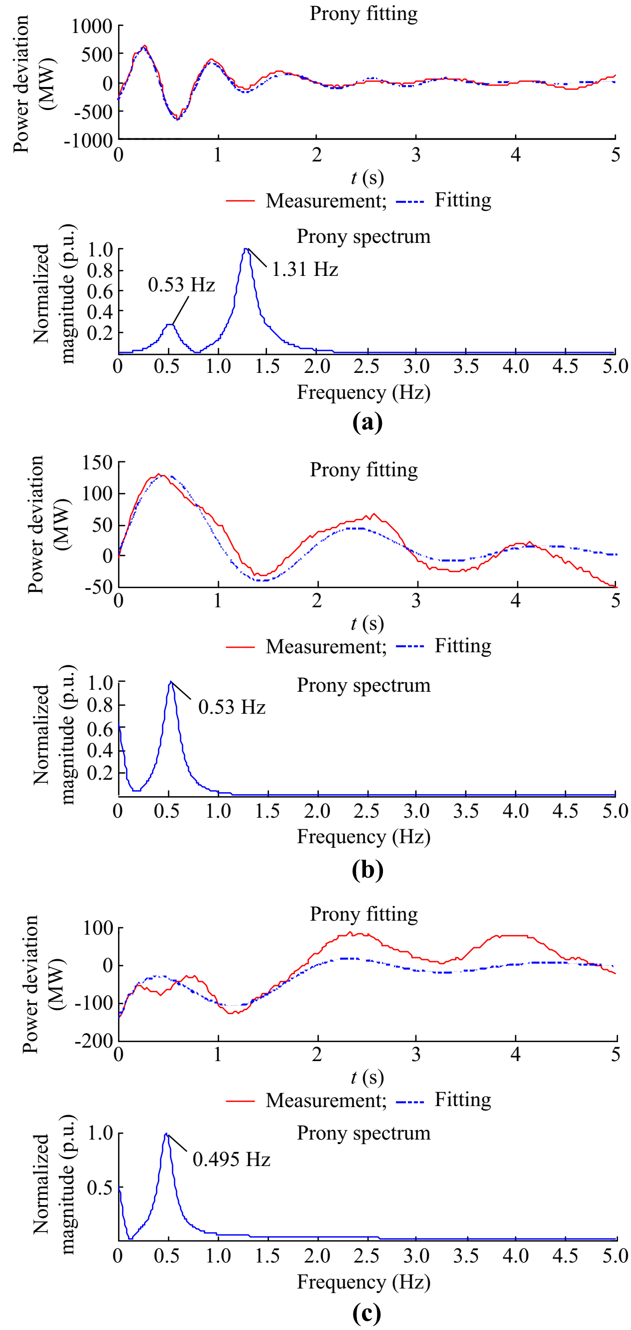


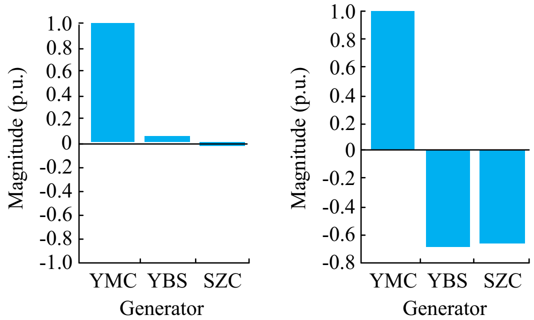
Fig. 6 Prony fitting and Prony spectrum of selected system signals

Table 4 Extracted modes of an actual event using SSI-DATA

Mode no.	Frequency (Hz)	Damping
1	1.3210	0.0962
2	0.5153	0.1384

6 Discussion

The multi-signal SSI-DATA technique requires a different interpretation paradigm from single-signal analysis methods, such as the Prony, HHT and Fourier spectral methos. The SSI-DATA provides the frequency, damping and the corresponded mode shape through eigen decomposition of the state matrix, and it calculates them at the



(a) 1.3210 Hz mode **(b)** 0.5153 Hz mode

Fig. 7 Mode shape of an actual event

same time. This is in contrast to the Prony, HHT and Fourier spectral methods, which process the multiple oscillating signals separately. Also, SSI-DATA does not require a pre-processing, such as de-noising, as measurement noise has already been considered in its formulation.

As shown in the study of an actual event, the SSI-DATA technique exhibits a good performance on generator active power oscillating signals, for both local and inter-area modes.

7 Conclusion

In this paper, the SSI-DATA technique is used to extract modal information from wide-area measurements. The advantage of the SSI-DATA technique in mode shape identification is that it estimates the state matrix and the output matrix spanning multiple generators in a power system from the measured data. Simulation results based on the IEEE 68-bus 5-area test system and actual event data showed that one of the prominent advantages of the proposed approach is the systematic determination of mode shapes while the frequency and damping of the modes are also accurately extracted. The proposed technique can be further explored and generalized for different applications and systems such as the design and optimization of low-frequency inter-area damping controller based on wide-area system measurements.

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